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Global Sensitivity Analysis of the BSM2 Dynamic Influent Disturbance Scenario Generator

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Abstract: The objective of this paper is to present the results of a global sensitivity analysis (GSA) of a phenomenological model that generates wastewater treatment plant (WWTP) dynamic influent disturbance scenarios. This influent model is part of the Benchmark Simulation Model no 2 (BSM2) and creates realistic dry/wet weather files describing diurnal, weekend and seasonal variations through the combination of different generic models blocks, *i.e.* households, industry, infiltration, rainfall and transport. The GSA is carried out by combining Monte Carlo simulations and standard regression coefficients (SRC), followed by classification of the influence of model parameters on the model output into strong, medium and weak. The results show that the method is able to decompose the variance of the model predictions (R^2 > 0.9) satisfactorily for several flow rate descriptors calculated at different time resolutions. Catchment size (PE) and the usage of wastewater per person equivalent (*QperPE*) are two parameters that strongly influence the yearly average dry weather flow rate and its variability. Wet weather conditions are mainly affected by three parameters: 1) the probability of occurrence of a rain event (*Llrain*); (2) the catchment size, incorporated in the model as a parameter representing the conversion from mm day^{-1} to m^3 day^{-1} (*Qpermm*); and, (3) the quantity of rain falling on permeable areas (*aH*). Very importantly, the case study shows that the SRC parameter ranking changes when the time resolution is changed, both for dry and wet weather conditions. The paper ends with a discussion on the interpretation of GSA results and of the advantages of using synthetic flow rate data for WWTP simulation studies. The discussion section also includes suggestions on how to use the influent model to adapt the generated time series to each modeller's demands.

Keywords: Activated Sludge Modeling, Benchmarking, BSM, Influent Modeling, Monte Carlo Simulations, Standard Regression Coefficients (SRC)

1. INTRODUCTION

Dynamic influent disturbance scenario generators (DIDSG) have recently gained interest in the field of wastewater treatment plant (WWTP) modeling. In essence, synthetic data can overcome one of the main limitations when performing simulation studies: A sufficiently long set of influent data representing the inherent natural variability of the flow rate and pollutant concentrations at the plant inlet is often not available. If inadequate dynamic influent disturbances are applied to the WWTP in a simulation study, the system will not be sufficiently excited and thus the simulations will result in a too optimistic picture of the plant performance (**Ráduly *et al.*, 2007).**

During the last years, several DIDSG have been developed with multiple applications. **De Keyser *et al.* (2010)** developed a model that creates time series of traditional and micro-pollutants from their emission sources in the urban catchment. Similarly, **Ort *et al.* (2005)** developed a stochastic model describing short-term variations of benzotriazole concentrations (a chemical in dishwasher detergents). Additionally, **Rosen *et al*. (2008)** used a Markov chain approach to describe the occasional occurrence of either toxic or inhibitory influent shock loads. One successful application of an influent wastewater generator was developed by **Gernaey *et al*. (2011),** and was used to generate influent data for the Benchmark Simulation Model no 2 (BSM2) (**Nopens *et al*., 2010**), a simulation benchmark widely used in the wastewater modelling community.

The BSM2 DIDSG is comprised of a set of generic model blocks and takes into account the contributions of households, industries, infiltration and run-off from impermeable surfaces. The model also includes the ‘smoothing’ effect of the sewer network. Although it is applied to create the disturbance influent file used to evaluate different control strategies in the BSM2 platform, the tool is rather general and has a wide range of applications. The software is intended to be flexible, but the full potential of the influent model can not be explored unless a comprehensive sensitivity analysis is made.

The purpose of this paper is to present the global sensitivity analysis (GSA) results of the BSM2 Influent Model Generator. The analysis is carried out by combining Monte Carlo (MC) simulations with Standard Regression Coefficients (SRC), and decomposes the variance of the flow rate predictions under different weather conditions. Finally, for different flow rate descriptors, calculated at different time resolutions, the influence of the model parameters on the generated flow rate data is classified into strong, medium and weak. The manuscript is organized as follows: First, the influent model, the parameter ranges and the different techniques for GSA are described. Next the results for both dry and wet weather conditions are presented. Finally, the study is complemented by a (critical) discussion of the results, with focus on the practical implications of the GSA results.

2. METHODS

2.1. Dynamic WWTP Influent Disturbance Scenario Generator

The DIDSG is based on the work presented in **Gernaey *et al.* (2011)**. The proposed phenomenological approach produces dynamic influent flow rate, pollutant concentrations and temperature profiles using different model blocks and it was used during the development of the BSM2. The influent data is assumed to correspond to the influent of a WWTP located in the Northern hemisphere, and is designed such that the evaluation period starts on July 1st. The first part of the influent data (245 days) has two purposes in the BSM2: the first 63 days are used to achieve a pseudo-steady state, whereas the next 182 days of data represents training data, *e.g*. for fine-tuning control algorithms before the start of the evaluation period.

For practical purposes, the analysis will be focused on the influent *flow rate*. The generation of the influent flow rate is achieved by combining the contributions of households (HH), industry (IndS), rainfall (Rain) and infiltration (Inf) (see **Figure 1)**. Rainfall contributes to the total flow rate in two ways: the largest fraction (*aH*/100) originates from the run-off of impermeable surfaces, and is thus transported directly to the sewer. Rainfall on permeable surfaces, a fraction (100 - *aH*)/100, will influence the groundwater level, and thus the contribution of infiltration to the influent flow rate. Assuming a cold and a warm season, the seasonal correction factor modifies the amount of infiltration, which is attributed to changes in the groundwater level over the year, *i.e.* different evapo-transpiration regimes. The seasonal correction factor is combined with the rainfall falling on permeable surfaces, and the sum of both flows is passed through the soil model. Afterwards, the net contribution of infiltration is combined with the overall flow rate resulting from households and industry and the flow contribution from rainfall on impermeable surfaces.

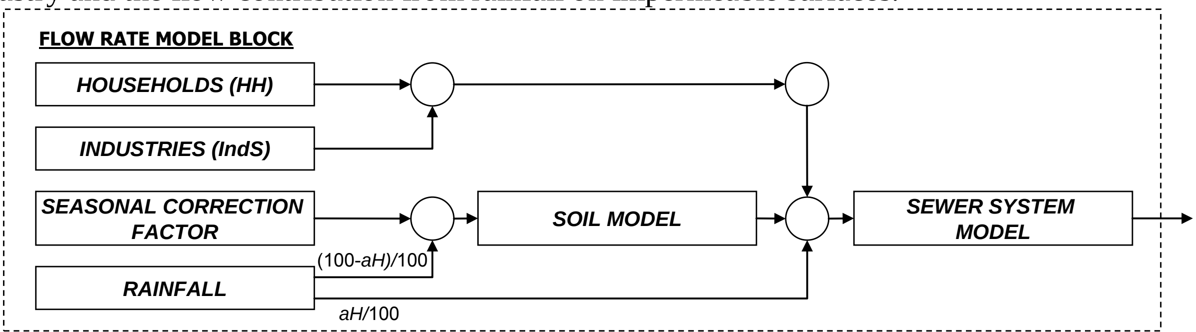

Figure 1. Schematic representation of the WWTP influent flow rate generator modeling approach (**Gernaey *et al.*, 2011**).

Figure 2 (left) shows a dynamic profile of the dry weather flow rate generated with the influent model using the default set of parameters. The flow rate time series presents daily, weekly and seasonal variation (*e.g*. holiday period and closing of industries). In addition, a slight increase of the flow rate during winter due to the effect of infiltration is visible. During the cold season, it is assumed that the groundwater level is high resulting in high infiltration to the sewer system. **Figure 2** (right) shows the dynamic profile of the wet weather flow rate generated with the influent model using the default set of parameters. Besides the above mentioned daily, weekly, yearly and seasonal phenomena there are sudden increases of the flow rate due to rain episodes.

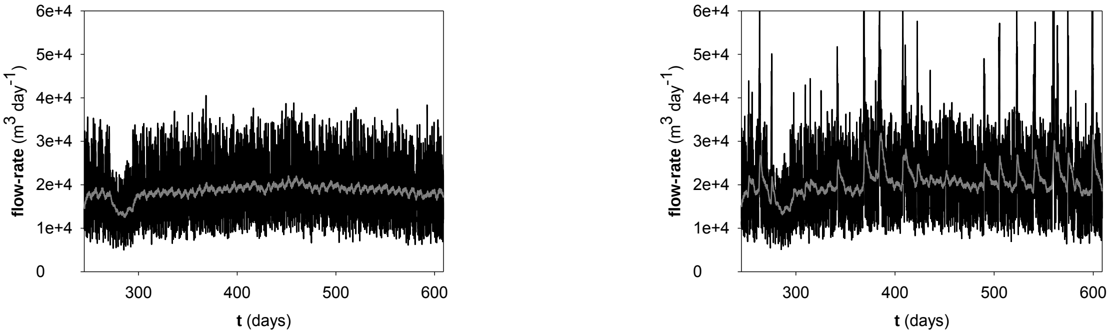

Figure 2. Dry (left) and wet (right) weather profiles generated with the influent model based on default parameters. An exponential filter (time constant of three days) is used to remove most noise variations for visibility purposes (grey).

2.2. MC simulation and SRCs

The MC simulation methodology is based on three steps: 1) specification of the input ranges, *i.e.* model parameters (**Table 1**); 2) sampling from the input ranges (**Iman *et al*., 1981**); and, finally 3) propagation of the sampled values through the model to obtain values for the outputs, *i.e.* flow rate descriptors (**Tchobanoglous *et al*., 2003**). The SRC method involves performing a linear regression on the output of the MC simulation revealing the relationship between the model parameters and the flow rate characteristics (**Saltelli *et al*., 2004**). The results of the GSA are then classified in three groups using k-means clustering (**Hair *et al*., 1998**) and characterized into strong, medium and weak influence on the output. Direct or indirect correlations are specified using positive (+) and negative (-) signs of the regression coefficients.

Table 1. Model (default) parameters and input ranges

	'Households (HH)' model block		
QperPE	Wastewater flow rate per person equivalent [$m^3.d^{-1}$]	150	±10%
PE	Person equivalent [-]	80000	±10%
	'Industry (IndS)' model block		
QInd	Average wastewater flow rate from industry on normal week days (Monday to Thursday) [$m^3.d^{-1}$]	2500	±10%
	'Seasonal correction factor (SCF)' model block		
InfAmp	Amplitude of the sine wave for generating seasonal effects due to infiltration [$m^3.d^{-1}$]	7100	±10%
InfBias	Mean value of the sine wave signal for generating seasonal effects due to infiltration [$m^3.d^{-1}$]	1200	±10%
	'Soil (SOIL)' model block		
H_{inv}	Height of the invert level [m]	2	±25 %
Subareas	Measure of the size of the catchment area [-]	4	±25%
K	Soil permeability constant [$m^3.m^{-2}.d^{-1}$]	1	±25%
K_{down}	Gain to adjust the flow rate to downstream aquifers [$m^2.d^{-1}$]	1000	±25%
	'Sewer system (SEWER)' model block		
Length	Length of the sewer system [-]	4	±25%
	'Rain generator (RAIN)' model block		
LLrain	A constant converting the random number generator output to a value representing rainfall intensities [mm rain.d^{-1}]	3.5	±50%
Qpermm	Flow volume per mm rain [$m^3.mm^{-1}$]	1500	±50%
aH	Direct contribution of rainfall falling on impermable surfaces in the catchment area to the flow rate in the sewer [%]	75	±50%

3. MC SIMULATIONS RESULTS

In **Table 2**, the respective distributions for all flow rate descriptors are summarized by their mean, coefficient of variation, 5% and 95% percentile value. The mean values of the average annual daily flow (AADF), the standard deviation (SD), the coefficient of shewness (CS), the coefficient of kurtosis (CK) and the hourly, daily and monthly maxima, minima and ranges are higher in wet weather conditions. However, comparatively, the relative differences between (dry / wet) Max average values are more extreme compared to the (dry / wet) Min values for the different statistics summarized in **Table 2**. For example, the dry / wet weather difference between average Max / Min flow rate values is 20%, 46%, 3% and 6, 4 and 3%, respectively. This is mainly due to: 1) the buffering effect of the soil model in the influent generator, and 2) the possibility to divert rain water directly (via run-off) into the sewer system (see **Figure 1**). The 5% and 95% percentiles can be interpreted in a probabilistic way, *e.g.* the 95% percentile of MaxH for the wet weather scenario means there is a probability of 95% that the average (hourly) flow rate is below 44338.9 $m^3.d^{-1}$. Finally, the differences between Max and Min (ranges) decrease when the temporal scale increases (for the different statistics). For example, the (mean) range of dry flow rate values is decreased down to 2370 $m^3.d^{-1}$ (from 20088 $m^3.d^{-1}$) when the scale is changed from hours (RangeH) to months (RangeM).

Table 2. Summary statistics of the MC uncertainty propagation

Item	Mean		Coefficient variation		5% percentile		95% percentile	
conditions	*DRY*	*WET*	*DRY*	*WET*	*DRY*	*WET*	*DRY*	*WET*
Average annual daily flow **(AADF)**	18569.9	20607.5	7.3	8.2	16316.4	18009.5	20879.4	23530.8
Standard deviation**(SD)**	6277.75	8300.1	10.63	15.8	5233.09	6421.4	7443.78	10769.6
Coefficient of shewness **(CS)**	0.36	2.5	32.49	31.7	0.18	2.1	0.54	3.0
Coefficient of kurtosis **(CK)**	2.50	5.9	6.18	27.0	2.28	3.6	2.75	8.8
Maximum hour **(MaxH)**	29498.8	35441.1	8.1	12.9	25759.5	28918.4	33650.0	44338.9
Maximum day **(MaxD)**	21276.8	30999.5	6.7	17.5	18909.5	23454.2	23720.1	40885.7
Maximum month **(MaxM)**	17694.3	18299.1	7.7	7.6	15412.9	15999.3	19971.5	20641.4
Minimum hour **(MinH)**	9410.7	9983.7	10.2	10.1	7804.8	8307.8	10937.4	11615.6
Minimum day **(MinD)**	15018.2	15560.0	8.5	8.3	12892.8	13439.4	17152.7	17719.1
Minimum month **(MinM)**	17694.3	18299.1	7.7	7.6	15412.9	15999.3	19971.5	20641.4
MaxH-MinH **(RangeH)**	20088.1	25457.4	10.4	16.9	16750.6	19501.7	23610.4	33885.3
MaxD-MinD **(RangeD)**	6258.6	15439.4	4.3	33.0	5841.4	8633.0	6703.4	24857.4
MaxM-MinM **(RangeM)**	2370.3	5027.5	4.8	28.8	2189.0	3209.2	2552.9	7790.4

4. GSA RESULTS

4.1. GSA of the WWTP influent generator during dry weather conditions

The parameters with the strongest influence on the dry weather flow rate are summarized in **Table 3**. AADF, MaxH, MaxD and MaxM are strongly (positively) influenced by the HH model block parameters (see effect on the total flow rate when the parameters *PE* and *QperPE* are increased in **Figure 3** left). These parameters represent the flow rate generated per person equivalent (*QperPE*) and the number of person equivalents in the catchment area (*PE)*. The length of the sewer system (*Length*) has a considerable effect on the standard deviation (SD), skewness (CS), kurtosis (CK) and MaxH/MinH/Range hourly values (see **Figure 3** right). When the value of the parameter *Length* is higher, the sewer system is assumed to increase in size and there is consequently a larger smoothing effect on the flow-rate values.

Table 3. GSA results (strong parameters, group 1 in k-means clustering) for dry and wet weather conditions. Negative (-) and positive (+) signs represent the correlation of the model parameters with the different evaluation criteria. In all the cases $R^2 > 0.9$.

Item	Dry weather	Rain weather
Average annual daily flow **(AADF)**	*PE* (+), *QperPE* (+), K_{down}(-), H_{inv} (-)	*Llrain* (-)
Standard deviation **(SD)**	*Length* (-), *PE* (+), *QperPE* (+)	*Llrain* (-), *Qpermm* (+), *aH* (+)
Coefficient of shewness **(CS)**	*Length* (-)	*Llrain* (-), *Qpermm* (+), *aH* (+)
Coefficient of kurtosis **(CK)**	*Length* (-)	*Llrain* (-), *Qpermm* (+), *aH* (+)
Maximum hour **(MaxH)**	*PE* (+), *QperPE* (+), *Length* (-)	*Llrain* (-)
Maximum day **(MaxD)**	*PE* (+), *QperPE* (+), K_{down} (-)	*Llrain* (-)
Maximum month **(MaxM)**	*PE* (+), *QperPE* (+), K_{down} (-)	*Llrain* (-),*PE* (+), *QperPE* (+), K_{down} (-), H_{inv} (-)
Minimum hour **(MinH)**	K_{down}(-), H_{inv} (-), *Length* (+)	H_{inv} (-), K_{down}(-), *Length* (+)
Minimum day **(MinD)**	K_{down}(-), H_{inv} (-), *PE* (+), *QperPE* (+)	H_{inv} (-), K_{down}(-), *PE* (+), *QperPE* (+)
Minimum month **(MinM)**	K_{down}(-), H_{inv} (-), *PE* (+), *QperPE* (+)	H_{inv} (-), K_{down}(-), *PE* (+), *QperPE* (+)
MaxH-MaxH **(RangeH)**	*Length* (-), *PE* (+), *QperPE* (+)	*Llrain* (-), *Length* (-)
MaxD-MaxD **(RangeD)**	*PE* (+), *QperPE* (+)	*Llrain* (-)
MaxM-MaxM **(RangeM)**	*InfAmp (+)*	*Llrain* (-)

The Seasonal Correction Factor (SCF) and the soil (SOIL) model parameters mainly influence the quantities of water (1) originating from upstream aquifers, (2) evapo-transpirated, (3) accumulated in soil, (4) passing to the sewer via infiltration and (5) diverted to downstream aquifers. The parameter *InfAmp* basically modifies process (2) and has a strong effect on RangeM and increases differences between winter and summer periods, corresponding to different evapo-transpiration regimes. Parameters H_{Inv} and K_{down} influence processes (3), (4) and (5) and have a strong impact on the quantity of water leaving the soil model block. As a result, there is a dramatic reduction of the infiltration flow to the sewer system and a consequent decrease of MinH, MinD and MinM. The rest of the SCF/SOIL model parameters show poor sensitivity. The limited amounts of Industrial wastewater compared to the HH contribution, makes the effect of IndS related model parameters almost unnoticeable.

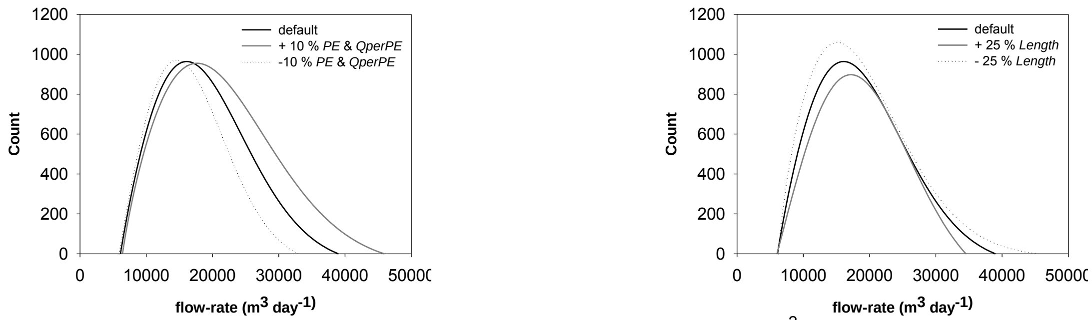

Figure 3. Distribution functions (Weibull) approximated from 75 bin histograms ($R^2 > 0.98$) showing (left) the effect on flow rate of HH parameters and (right) the effect of SEWER parameters.

4.2. GSA of the WWTP influent generator during dry weather conditions

RAIN related model parameters (*Qpermm*, *LLrain* and *aH*) have a strong impact on the total flow-rate quantity and variability (see **Table 3** and **Figure 2**). On one hand, *Llrain* increase/decrease the probability of having rain events. On the other hand, *Qpermm* and *aH* strongly influences the 1) intensity of these wet events, 2) quantity of water entering the soil and 3) quantity of water going directly to the sewer (see **Figure 1**).

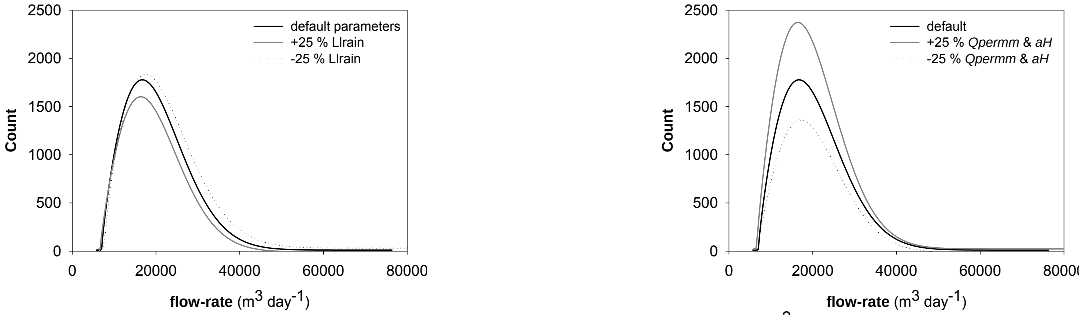

Figure 4. Distribution functions (Weibull) approximated from 75 bin histograms ($R^2 > 0.98$) showing (left) the effect on flow rate of *Llrain* and (right) of *Qpermm* and *aH* parameters.

As can be expected when the number of rain events is increased (*Llrain* increases), AADF, SD and RangeH, D and M values are higher (see **Figure 4** left). *Qpermm* and *aH* have a major influence on the shape of the resulting flow rate distribution, *i.e.* increasing its asymmetry (CS) and peak height (CK) (**Figure 4** right). This is mainly due to the fact that most of the flow rate values are moved to the right-hand side of the distribution. It is important to highlight that RAIN related parameters have a strong influence on flow rate descriptors that are sustained for a short period of time, for example MaxH and MaxD (peak values). For longer periods of times, *i.e.* MaxM and MinM, the parameters with the strongest impact are the same for both wet and dry weather conditions, *i.e.* HH and SOIL. Finally, minimum values, *i.e.* MinH, MinD and MinM, are strongly influenced by the soil model parameters, similar to dry weather conditions. Again, it is possible to see the buffer effect of the soil model. Unless there is either a dramatic decrease in the quantity of water accumulated by the soil (parameter H_{INV}) or an increase in the quantity of water going to downstream aquifers, minimum values are more or less constant for both dry and wet weather conditions (see **Table 2**).

5. DISCUSSION

The presented results necessitate a thorough discussion. First of all, the GSA provides a better picture about how the DIDSG behaves, by determining the strength of the relation between the input ranges (model parameters) and the different outputs (flow rate descriptors in this case). As a result, it is possible to interpret the GSA in order to learn how to use the influent model to adapt the generated time series to each modeller's demands. For example, **Figure 5** shows the effect (for dry weather flow rate) of some model parameters on the flow rate descriptors. SCF parameters can increase the monthly differences between summer and winter time (see **Figure 5** top, **Table 3** RangeM). The parameters *PE* and *QperPE* increase ADDF, MaxH, MaxD and MaxH (see F**igure 5** middle**, Table 3**). Finally, a stronger smoothing effect can be obtained if the length of the sewer network is increased (**Figure 5** bottom, **Table 3** MaxH). In wet weather conditions, the periodicity of rain events is mainly determined by the parameter *Llrain* (see **Figure 6***)*. In case of using pluviometric data as input – an option that is available for the user of the influent model – the parameter *Llrain* is no longer used and the adjustment should be carried out by means of modifying the parameters *aH* and *Qpermm.* As in the dry weather case, hourly peaks in the wet weather scenario can be influenced by adjusting the parameter *Length.*

Other interesting potential applications for model-based generation of dynamic influent flow rate profiles are: a) filling the gaps in dynamic influent data time series; b) giving a dynamic character to data sets consisting of composite influent samples; and c) creating additional disturbance scenarios following the same catchment structure. A clear example of applications a) and b) is provided in **Figure 5**, where it is possible to see how starting from available monthly data, realistic daily and hourly influent flow rate profiles can be created.

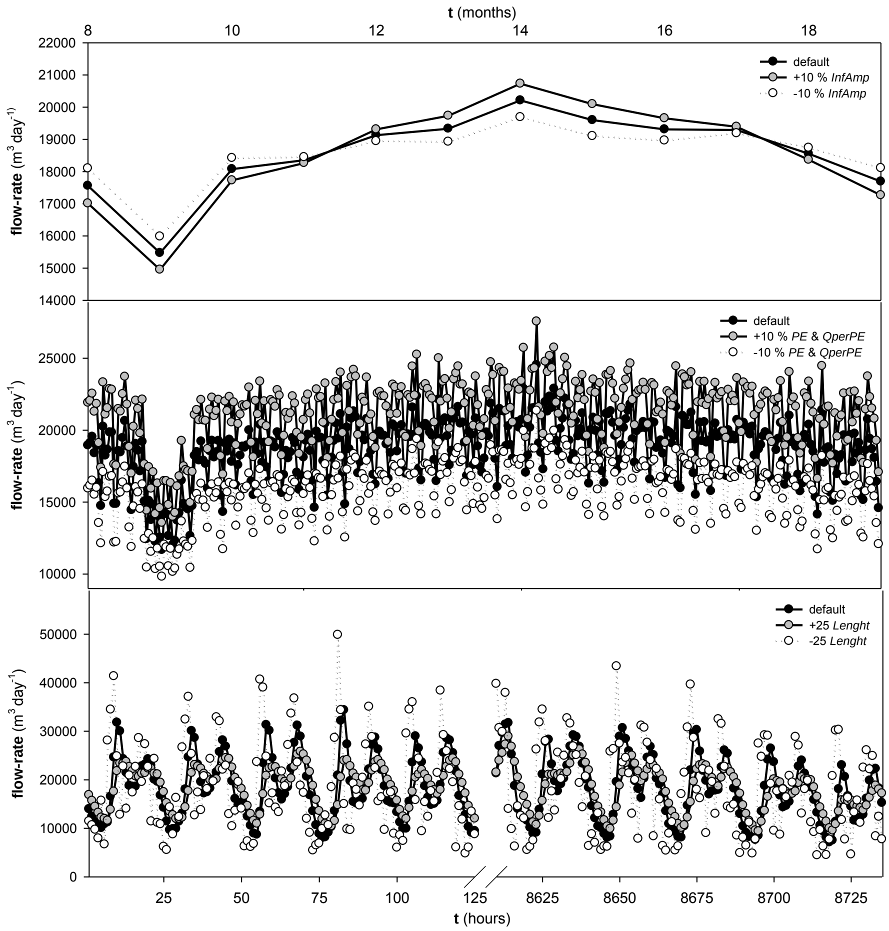

Figure 5. Effects of the parameter SCF (a), the HH model block (b) and the SEWER model block (c) on the dynamic flow rate at different temporal resolutions: monthly (a), daily (b) and hourly (c).

The modelling concepts behind the generic blocks incorporated in the BSM2 DIDSG supplemented with the knowledge gained after performing the presented GSA, represent a valuable tool for scientists, process engineers and water professionals because it will allow answering practical questions such as: What would be the effect of changing the rain regime or the infiltration dynamics (due to for example climate change) on the generated influent flow rate profile, or what is the effect of a population increase (changes in the number of population equivalents) on the influent flow rate profile? Such dynamic influent scenarios can be used in combination with traditional simulation-based WWTP scenario analysis, in order to obtain more realistic predictions of the effect of, for example, climate change or a change in the size of the population in the catchment on the simulated WWTP performance.

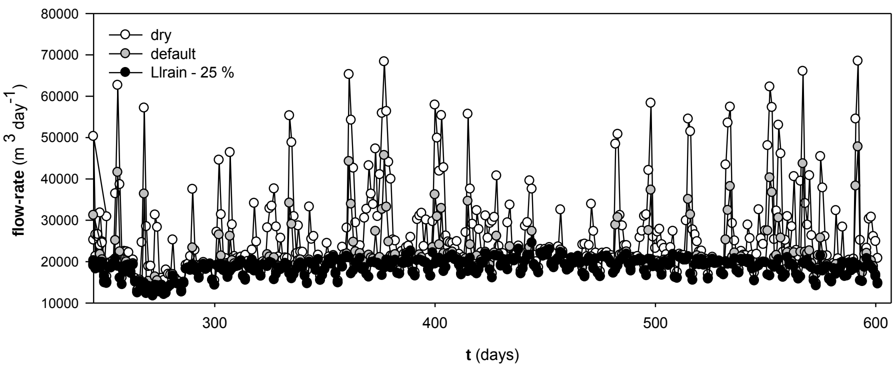

Figure 6. Effect of the parameter *Llrain* on the dry and wet weather influent flow rate profile.

It is also important to point out that the results of the GSA will to a large extent depend on the framing of the problem (selection of model parameters, definition of uncertainty ranges, sampling methodologies) (**Sin *et al*., 2011**). The results of the GSA presented in this paper are specific for this case study and they should be interpreted within that context, *i.e.* the analysis would have to be repeated if we apply the influent generator for a totally different case study.

5. CONCLUSIONS

This paper presented the results of performing a Global Sensitivity Analysis on the output of a DIDSG. The high R^2 values showed that variance decomposition for a range of different flow rates was possible. The key findings can be summarized as follows:

In dry weather conditions:

1) HH parameters (*QperPE*, *PE*) have the strongest influence on dry weather influent flow quantity and variability. The sewer parameter *Length* has a direct influence on the peaks;
2) SCF (*InfBias*) and SOIL related (H_{inv}, K_{down}) parameters influence the quantity of a) infiltration and b) water accumulation in soil, decreasing (to a certain extent) average, ranges and minimum flow rate values.

In wet weather conditions:

1) RAIN related parameters (*LLrain*, *Qpermmm* and *aH*) have a strong influence on wet weather influent flow rate quantity and variability;
2) RAIN related parameters (*LLrain*) clearly affect short-term evaluation criteria (hour, day), but in the long run (month) the HH related parameters have a stronger influence;
3) SOIL related parameters (H_{inv}, K_{down}) influence (as for dry weather conditions) minimum values, no matter the time scale.

The GSA has been extended with: i) a section focused on the advantages of using synthetic flow rate data for WWTP simulation studies, ii) some hints on how to use the influent model to adapt the generated time series to each modeller's demands and iii) a critical discussion about how to interpret the results of the GSA.

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